CLASSIFICATION OF RADAR IMAGERY OVER BOREAL REGIONS FOR METHANE EXCHANGE STUDIES

Stephen L. Durden[1], Ziad S. Haddad[1], Leslie A. Morrissey[2], and Gerald P. Livingston[2]

[1]Jet Propulsion Laboratory
California Institute of Technology
4800 Oak Grove Dr
Pasadena, CA 91109

[2]TGS Technology, Inc.
NASA Ames Research Center
Moffett Field, CA 94035

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Abstract

NASA/JPL AIRSAR data were acquired over Minto Flats, Alaska on 18 July 1993. These data were used to investigate the ability of multifrequency, multipolarization SAR to distinguish vegetative communities and the presence of standing water, parameters directly related to methane exchange rates. Boreal communities were accurately differentiated using both statistical and neural network classification techniques applied to fully polarimetric L and C band data. Similar classification accuracies were also obtained using a non-polarimetric subset of the data, analogous to data that would be available from combining observations from JERS-1, ERS-1, and RADARSAT.

1 Introduction

Northern ecosystems represent a complex heterogeneous mixture of methane producing source and consuming sink areas. Because of the size and inaccessibility of northern ecosystems, their precise contribution to the global methane budget is uncertain. Currently, remote sensing technology for directly monitoring surface methane exchange rates is not available. However, it may be possible to indirectly monitor methane exchange rates by remotely sensing vegetation type and presence or absence of surface water, factors well correlated with methane emission (Morrissey and Livingston 1992). Synthetic aperture radar (SAR), in particular, appears to be well-suited for this application (Morrissey et al. 1994). The ability of SAR to detect surface water beneath vegetation has been well documented (Hess et al. 1990). Recent studies also suggest that SAR can distinguish wetland vegetation types (Pope et al. 1994). Because of the existence and plans for several spaceborne missions (ERS-1 and 2, JERS-1, RADARSAT, ENVISAT), SAR offers the possibility of providing a means of spatially integrating hydrologic and vegetative parameters corresponding to methane exchange on local to regional scales (Morrissey et al. 1994). Furthermore, multiple SAR observations could provide information on changes through the growing season and between years.

In this paper, we investigate the ability of multipolarized multifrequency SAR to distinguish vegetation types and the presence or absence of standing water in a boreal setting as they relate to methane exchange. We describe the data used in this study and then present results of using both statistical and neural network classifiers. Results are presented for both the fully polarimetric radar parameter set and for non-polarimetric subsets, such as would be produced by ERS-1, JERS-1, and RADARSAT.

2 Data Description

The data used in this study were acquired over Minto Flats, Alaska, on [illegible]8 July 1993, using the NASA/JPL DC-8 AIRSAR polarimetric radar (Freeman et al. 1990). Because of severe interference at P-band, only L-band and C-band data are used in this study. The data used here have been averaged to 64 looks, to reduce speckle noise, resulting in a resolution of approximately 50 m. Because Minto Flats is composed of extensive wetlands, there is almost no variation in topography within the image. The time of the data acquisition was near the peak, mid-summer growing season, as determined by visits to the site. Additional ground truth for the area was determined from US Geological Survey and US Soil Conservation Service maps of the area.

At the time of the AIRSAR acquisition, the area was divided into four classes with respect to methane exchange rates, based on previous field measurements. Highest emissions were from fens, which are herbaceous sedges and grasses with standing surface water. Second highest emissions are from bodies of water without vegetation, e.g., lakes and ponds. The third class is bogs, which consist of low-lying shrubs with a black spruce overstory and intermittently waterlogged soil. This class can represent a low methane source or weak sink, depending on the position of the local water table. The fourth class consists of well drained forest and tall shrub areas. Areas belonging to this class have zero methane emission; they often absorb very small quantities of methane. Table 1 shows the environmental characteristics of each of the four classes, including typical methane exchange rate (Morrissey et al. 1994).

Table 2 shows the mean of the L- and C-band HH and VV cross sections σ^o, HH/VV polarization ratio P[illegible] HV/HH linear depolarization ratio LDR, HH-VV correlation coefficient ρ, and HH-VV phase difference α for each class. The standard deviation of the cross sections and their ratios is approximately 2 dB, the standard deviation of ρ is approximately 0.15, and the standard deviation of α is approximately 60^o. Note that for 64 looks, the standard deviation of the cross section due to speckle alone should be 0.5 dB. The 2 dB standard deviation noted here is probably related to spatial variability of the vegetation and hydrology within classes. The incidence angle for the data ranges from 30^o to 50^o, and little dependence of radar parameters with incidence angle was noted.

3 Classification Methods

Classification of SAR imagery has been approached using both statistical and neural network algorithms, and we examine both of these techniques for our application. For the statistical classifier, we follow the work of (Rignot and Chellapa 1992) who developed a maximum *a posteriori* (MAP) classifier. The MAP classifier for the complete image is found by maximizing the probablity density function (PDF) of the pixel labels conditioned on the radar observations. Applying Bayes' rule to this PDF yields

$$p(L|X) \propto p(L)p(X|L) \tag{1}$$

where X is the array of radar data and L is the array of pixel labels. Following (Rignot and Chellapa 1992), $p(L)$ is found by modeling the labels as a Markov Random Field, where the conditional probability of the label at a single pixel depends only on the labels of the immediate neighborhood of the pixel. Again following (Rignot and Chellapa 1992), $p(X|L)$ is assumed to be the product of the conditional PDFs for each pixel $p(x|l)$. However, while Rignot and Chellappa assumed that variance in the radar characteristics is determined entirely by speckle, we choose to allow each radar parameter to have an empirically determined variance. Assuming Gaussian statistics and diagonal covariance matrix,

$$p(x|l=i) = z\exp\left(-1/2\sum_j \left[(x_j-\mu_{ij})^2/\sigma_{ij}^2\right) - 1/2\prod_j \sigma_{ij}^2\right) \tag{2}$$

where z is a constant, and μ_{ij} and σ_{ij}^2 are the mean and variance, respectively, of the jth element of the parameter vector x for class i. The Gaussian assumption should be reasonably accurate for many look data. The diagonal covariance matrix assumption can be approximately satisfied if the parameters are chosen properly. This is the case for the parameters used in the next section. The MAP classifier is implemented by first finding $p(X|L)$. If L is found by maximizing this function alone, the result is the maximum likelihood (ML) solution. The MAP solution is then found by using the ML solution as the initial L in a simulated annealing procedure (Press et al. 1992) which maximizes $p(L)p(X|L)$.

Neural networks have also been applied to the radar classification problem (Hara et al. 1994). The neural network (NN) approach has the advantage of being non-parametric: no assumptions about the underlying probability structure are made. To perform the neural network classification, we chose a three-layer, feedforward neural network (Lippmann 1987) and used backpropagation for training. The network has a number of input nodes equal to the number of radar parameters, 20 nodes in the hidden layer, and 4 output nodes (corresponding to the four classes in Table 1). As implemented here, the neural network classifies each pixel based only on the radar parameters at that pixel. Correlations between pixels are not considered, similar to the ML statistical classification.

4 Results

A training set consisting of 381 64-look samples was developed. The radar parameter vector consists of the radar parameters LHH σ^o, LPR, LLDR, Lρ, Lα, CHH/LHH σ^o ratio, CPR, CLDR, Cρ, and Cα.

The cross sections and their ratios are expressed in dB. The statistical and neural network classifiers were trained and were then tested on a set of 64 look test sites that were adjacent to the training sites. Because the model for $p(L)$ requires the full image, the ML classifier rather than MAP classifier was used on the test sites. The resulting confusion matrices are shown in Table 3. The overall classification accuracy is 81% for both classifiers. Both were able to reliably detect forests, fens, and open water. Bogs were often misclassified as forest. As can be seen in Table 2, the characteristics of bogs and forests appear to be very similar, so the confusion is not suprising. We also examined data acquired on May 7 1991, just as snow was melting. In this scene many of the bogs have very low backscatter relative to forests. This suggests that an improvement in classification accuracy may be obtained by using data acquired at multiple times. Such time series data should be routinely available from spaceborne SAR.

Next, we applied both the statistical and neural network techniques to the full radar image. The ML and NN classifiers produced similar results, with the ML being somewhat better. The MAP classifier, however, produced significantly better results since it takes into account the correlation between pixel labels. The results for the MAP classifier are shown in Figure 1. The high producing methane fens are shown in white, while forests are black. The bog areas are dark gray, and open water is light gray. Many of the fens surround open water, as would be expected. The classification map in Figure 1 is in good agreement with our ground truth information.

Finally, it is of interest to examine the accuracy of classification using only those measurements that would be available from the JERS-1, RADARSAT, and ERS-1 satellites, namely the backscatter cross sections σ^o at LHH, CHH, and CVV. Table 4 shows the resulting confusion matrices for ML classification using only σ^o measurements. LHH results are very similar to the fully polarimetric case in Table 3, except that the classification of bogs is less accurate. The overall accuracy is 78%, as compared to 81% for the fully polarimetric case. As compared with LHH, CHH data has a much lower classification accuracy for fens. CVV (not shown) is quite similar to CHH. To the right of the CHH case are the results of using two input parameters, namely, LHH and the CHH/LHH ratio. The results are quite similar to the LHH case in Table 4, except that the bog classification is slightly improved. To the right of this case are the results CHH and CVV/CHH. The results are similar to the case of using only CHH or CVV. The accuracy of the forest classification is lower but classification of fens, and particularly bogs, is improved. Finally, results for LHH, CHH/LHH, and CHH/CVV are shown at the far right in Table 4 and are similar to using LHH only, except that the accuracy of the bog classification is improved. The overall accuracy is 81%, identical to the fully polarimetric case for both ML and NN classifiers. We also used these parameters for MAP classification of the entire image (not shown) and found results very similar to Figure 1

5 Conclusions

We acquired AIRSAR data over various Alaskan boreal ecosystems as part of an effort to evaluate the potential of SAR in ecosystem process studies which require classification of vegetation types and presence or absence of standing water. We examined the multi-frequency, multi-polarization signatures or four vegetation classes: upland forests and tall shrublands, shrub bogs, open water, and fens. These range from near zero methane emission to very high methane emission. Using fully polarimetric L- and C-band data, the Maximum *a Posteriori* classification) method produced good results, separating all four classes, The high methane emitting fen class was particularly well separated. The least accurately classified class was bogs, due to their similarity to forests. It was noted that use of data at other times of the year may improve the classification of bogs. This possibility should be further investigated using satellite SAR data.

Tests were run to determine whether parameters available from one or more non-polarimetric radars could also be used to separate the four vegetation classes. The classification results using only the LHH, CHH, and CVV cross section data were very similar to the fully polarimetric case. Furthermore, accurate classification of fens, water, and forest was obtained using LHH data only. These results confirm the utility of SAR data in methane exchange studies and suggest that useful results can be obtained with systems that are already in operation or will be in the near future.

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Figure Captions

Figure 1. Classification of fully polarimetric L- and C-band imagery using MAP classifier. Black is forest and tall shrub. Dark gray is shrub bog. Light gray is open water, and white is fen.

Class	Description	Drainage	Methane Emission (mg m^{-2} hr^{-1})
1) Forest	deciduous and coniferous forests tall alder and willow shrublands	well drained	0.0
2) Bog	black spruce and shrub bogs with tussocks	poor	0.4
3) Water	open water in lakes and ponds		1.0
4) Fen	herbaceous grasses and sedges	poor	20.0

Table 1: Vegetation Classes

Class	L-band						C-band					
	σ^o_{HH} (dB)	σ^o_{VV} (dB)	PR (dB)	LDR (dB)	ρ (deg.)	α (dB)	σ^o_{HH} (dB)	σ^o_{VV} (dB)	PR (dB)	LDR (deg.)	ρ	α
1) Forest	-7.9	-8.3	0.4	-6.7	0.34	4	-5.4	-6.0	0.6	-6.2	0.41	-4
2) Bog	-7.8	-7.7	-0.1	-7.0	0.39	-16	-4.1	-5.2	0.9	-6.9	0.35	-3
3) Water	-27.7	-25.4	-2.3	-10.0	0.37	-18	-23.7	-22.3	-1.4	-6.5	0.26	-7
4) Fen	-14.7	-13.7	-1.0	-7.6	0.27	31	-5.4	-5.8	0.4	-7.3	0.25	52

Table 2: Mean Radar Parameters for the Vegetation Classes

True Class	Assessed Class ML 1	2	3	4	Assessed Class NN 1	2	3	4
1	61	17	0	0	75	3	0	0
2	23	30	0	5	24	32	0	2
3	0	0	54	1	0	0	54	1
4	13	12	0	165	13	30	0	147

Table 3: Confusion Matrices for ML and NN Using Polarimetric Data